WIND PREDICTION ACCURACY FOR AIR TRAFFIC MANAGEMENT DECISION SUPPORT TOOLS*†

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ABSTRACT

Air traffic automation depends on accurate trajectory predictions. Flight tests show that wind errors are a large source of error. Wind field accuracy is sufficient on average, but large errors occasionally exist that cause significant errors in trajectory prediction. A year-long study was conducted to better understand wind prediction errors, to establish metrics for quantifying large errors and to validate two approaches to improve wind prediction accuracy.

Three methods are discussed for quantifying large errors: percentage of point errors that exceed 10 m/s, probability distribution of point errors, and the number of hourly time periods with a large fraction of errors above a threshold.

The baseline wind prediction system evaluated for this study is the Rapid Update Cycle (RUC). Two approaches to improving the original RUC wind predictions are examined. The first approach is to enhance RUC in terms of increased model resolution, improved model physics, and increased observations. The second method is to augment the RUC output, in near real time, through an optimal interpolation scheme that incorporates the aircraft reports received since the last RUC run. Both approaches are shown to greatly reduce the occurrence of large wind errors.

1. SUMMARY

Air Traffic Management (ATM) Decision Support Tools (DST) require accurate trajectory predictions to provide controllers with operationally acceptable advisories. Flight tests have shown that wind prediction errors are the largest source of trajectory prediction error. Although on-average wind prediction accuracy may be sufficient, these flight tests revealed that large errors occasionally exist over large enough regions of airspace and time to cause significant errors in trajectory predictions. Such errors, even if they occur only infrequently, significantly diminish the operational acceptance of ATM DST advisories. A year-long study of the Denver Air Route Traffic Control Center (ARTCC) airspace was conducted to better understand the magnitude and source of wind prediction errors, to establish metrics for quantifying large errors that may be critical to ATM decision support, and to validate two approaches to reducing the occurrence of these large errors.

Three methods are discussed for measuring large errors, given spot checks of wind accuracy from comparisons to aircraft measured winds at a set of points. The first, large point error percentage, indicates the percentage of point wind vector errors that exceed 10 m/s. The value 10 m/s is taken as a threshold at which wind errors become problematic for an ATM DST. The second, error probability distribution, looks at the distribution of point wind vector errors. This metric offers greater flexibility in that no *a priori* threshold is applied. The third method, large hourly error, determines the number of hourly time periods within which a certain percentage of point errors exceed a threshold; for example 10 m/s. The advantage of this metric is its applicability to determining the frequency of periods within which ATM DSTs may be negatively impacted by groups of large point errors since a single point error does not lead to poor trajectory accuracy.

The baseline wind prediction system evaluated for this study was the Rapid Update Cycle (RUC). Two approaches to improve the original RUC wind predictions are examined. The first approach is to enhance RUC in terms of increased model resolution, improved model physics, and increased observational

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† Opinions, interpretations, conclusions, and recommendations are those of the author and are not necessarily endorsed by the United States Air Force. Corresponding author address: Rodney E. Cole, Massachusetts Institute of Technology, Lincoln Laboratory, 244 Wood Street, Lexington, Massachusetts 02420-9185; e-mail: rodc@ll.mit.edu

input data. The second method is to augment the RUC output, in near real time, through an optimal interpolation scheme that incorporates aircraft reports received since the last RUC update. Both approaches are shown to greatly reduce the occurrence of large wind errors. For example, the improvement in the RUC model reduced the percentage of point errors greater than 10 m/s from 8% to 3%, and the augmentation of RUC with near real-time aircraft reports reduced such errors from 11% to 4% (using a slightly different set of RUC forecasts.)

2. INTRODUCTION

The performance of Air Traffic Management Decision Support Tools depends in large part on the accuracy of the supporting 4D trajectory predictions. Accurate trajectory predictions are particularly critical for conflict prediction and for systems providing active adivisories. Flight test results have indicated that wind prediction errors may represent the largest source of trajectory prediction error (Williams and Green, 1998; Jardin and Green, 1998). The tests also discovered relatively large errors (e.g., greater than 20 knots or 10 m/s), existing in pockets of space and time critical to ATM DST performance (one or more sectors, greater than 20 minutes). Classic RMS aggregate prediction accuracy statistics, most often used in past studies, inadequately represent these operationally significant errors.

To facilitate the identification and reduction of wind prediction errors that might lead to poor DST performance, NASA is leading a collaborative research and development activity with MIT Lincoln Laboratory (MIT/LL) and the National Oceanographic and Atmospheric Administration (NOAA) Forecast Systems Lab (FSL). This activity began in 1996 and is focused on the development of key wind error metrics for ATM DST performance, assessment of wind prediction accuracy for state-of-the-art systems, and development/validation of system enhancements to improve accuracy. A year-long study was conducted for the Denver Center airspace in 1996-1997.

Two complementary wind prediction systems are analyzed and compared to the forecast performance of the (then standard) 60-km Rapid Update Cycle - version 1 (RUC-1). The RUC is a mesoscale numerical weather prediction model (Schwartz and Benjamin, 1998) developed by NOAA. The first system analyzed is the prototype 40-km RUC-2. The RUC-2 became operational at the National Center for Environmental Prediction (NCEP) in 1999. The RUC-1 runs every three hours, producing a set of hourly forecasts, and the RUC-2 runs hourly producing a set of hourly forecasts. In addition to a finer resolution grid than used by RUC-1, RUC-2 uses more sophisticated physics and additional observations.

The high-frequency atmospheric observations which allow the rapid RUC update rate include those from commercial aircraft equipped with Aircraft Communication Addressing and Reporting System (ACARS), wind profiles from various vertically pointing radars, surface observations, and estimates of moisture and winds from satellites. The RUC horizontal domain covers the Continental United States and adjacent parts of Canada, Mexico, and oceanic areas. The initial operational version of the RUC was implemented at NCEP in September 1994 with a 60 km horizontal resolution. A major upgrade was implemented in April 1999 as the 40-km RUC-2.

The second system studied, Augmented Winds (AW), is a prototype en route wind application developed by MIT Lincoln Laboratory based on the Terminal Winds analysis (Cole, et al., 2000) developed for the FAA's Integrated Terminal Wind System (ITWS) (Evans and Ducot, 1994). AW is designed to run at a local facility (Center) level. The Terminal Winds is a data assimilation system that uses RUC wind forecasts and recent local measurements of the wind to produce estimates of the current wind field. These local measurements can come from surface observing systems, FAA and NWS Doppler weather radars, and ACARS.

The ITWS Terminal Winds system produces two wind fields: one with a horizontal resolution of 10 km which updates every 30 minutes, and one with a horizontal resolution of 2 km which updates every five minutes. The 2-km resolution grid is nested within the 10-km resolution grid. The algorithm starts with an initial estimate and modifies it to agree with the observations in a general least squares sense via the Gauss-Markov Theorem (Luenbuger, 1969). This scheme is closely related to traditional Optimal Interpolation and variational techniques (Daley, 1991). The Augmented Winds analysis consists of only the 10 km analysis fed RUC-1 on the hour, and near real-time aircraft (ACARS) wind reports. Due to the 3-hour run cycle of RUC-1 and the model run time, the 3-5 hour RUC-1 forecasts are used.

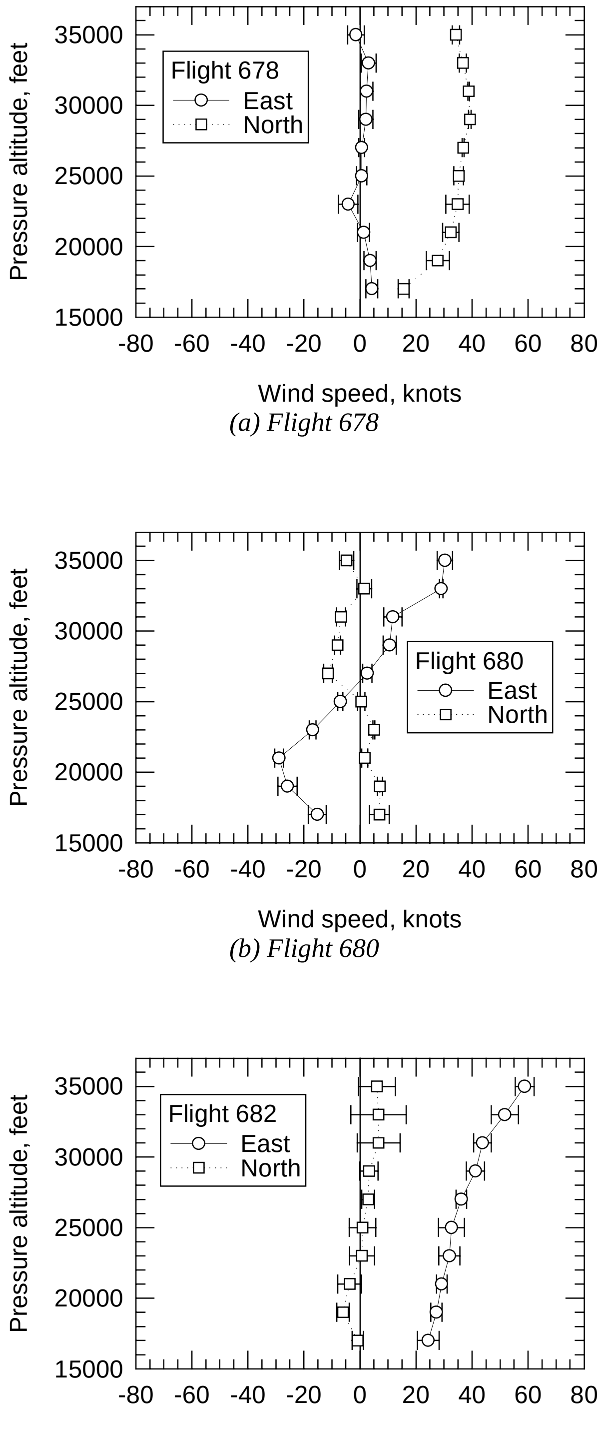
3. FLIGHT TEST RESULTS USING RUC-1

As part of an overall NASA effort to research and develop integrated user Flight Management System (FMS) and ATM Decsion Support Tools such as the Center TRACON Advisory System (CTAS), (Denery and Erzberger, 1995), a series of flight tests were conducted at the Denver Center in 1992 (phase I) and 1994 (phase II). These tests were conducted to validate airborne and ground-based (ATM/CTAS) trajectory prediction accuracy, identify and measure major sources of trajectory prediction error, and explore procedures for the integration of FMS and CTAS decision support tools for arrival traffic (Williams and Green, 1998; Green, et al., 2000). A key finding of those tests was that wind prediction error was the greatest source of error for trajectory predictions on the order of 20 minutes time horizon (critical to ATM DST advisories for conflict prediction/resolution and conformance to flow rate/metering constraints).

Phase I involved 24 test runs conducted over five flight routes over five days. The phase II test involved 26 test runs conducted over five flight routes over seven days. Each test run involved a 100-200 nmi. arrival path, including a cruise segment (FL350 or 330) followed by a descent segment (to 17,000 or 18,000 ft.) to the Denver terminal area. The phase I test involved arrival runs from the northeast standard arrival route (arrival course of 237 degrees true), while the phase II test involved arrival runs along the northwest standard arrival route (initial course of 090 degrees true followed by a turn to 145 degrees true approximately 30 nmi. prior to the end of the test run at the terminal area boundary). Typical test flights included 5 runs during approximately a 3-hour time period.

Forecasts of winds were received every three hours from the Mesoscale Analysis and Prediction System (MAPS, the RUC-1 prototype system) operated out of NOAA Forecast System Laboratory. CTAS converted the MAPS data into local Denver-Center system coordinates and interpolated the data to determine the predicted winds aloft along a flight path predicted by CTAS. These interpolated winds along the flight path were recorded for each test run. The actual winds were measured and recorded once per second, with smoothing, on board NASA's Transport Systems Research Vehicle (TSRV) a Boeing 737. GPS was used for inertial velocity, and the flight test air data system was used for air-mass velocity.

The measured winds of sample phase I and phase II flights are presented in figures 1 and 2, respectively. The winds along path are presented in terms of component speeds (knots) in the true north and east directions. For consistency between runs, the data are presented as a function of pressure altitude, with samples at discrete levels. Data from the multiple runs of each flight are combined into a mean and standard deviation of wind speed at that altitude. Data for the cruise altitude include all samples taken at cruise during the run, whereas data for lower altitudes include a single sample for each run as the flight passed through that altitude. Figures 1 and 2 illustrate a relatively large variation in the winds aloft between flights, with some variation within a flight (across multiple runs).

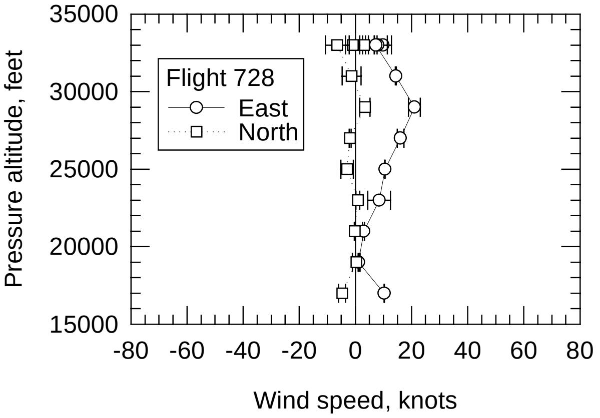


(a) Flight 678

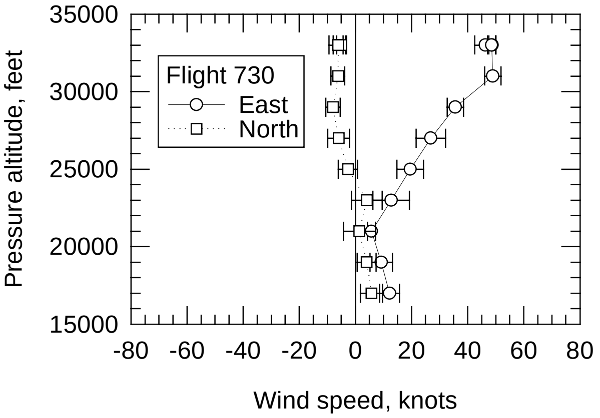
(b) Flight 680

(c) Flight 682

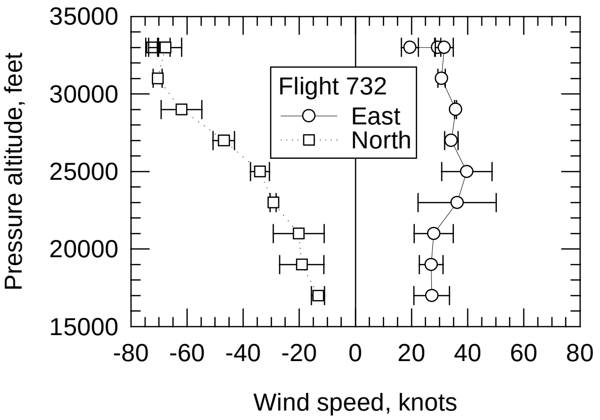
Figure 1. Measured winds from the phase I test.



(a) Flight 728



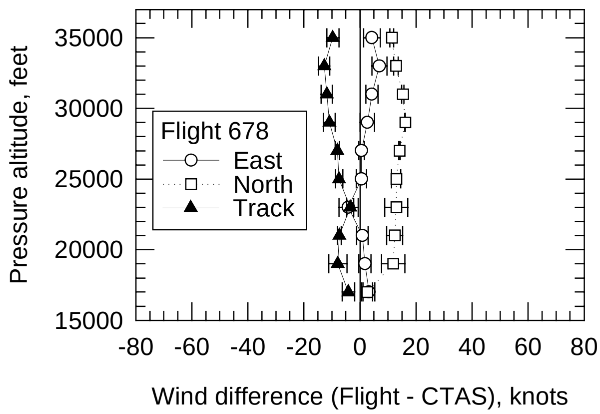
(b) Flight 730



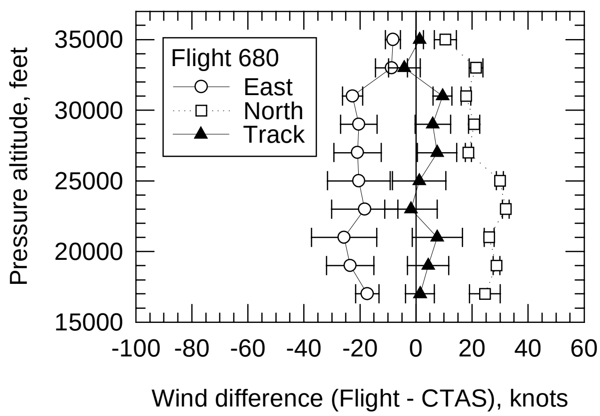
(c) Flight 732

Figure 2. Measured winds from the phase II test.

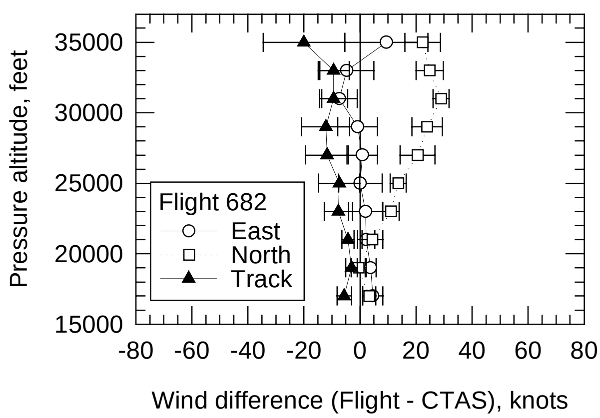
A sample of the measured/analyzed wind prediction errors are presented in figures 3 and 4 for phase I/II, respectively, using a similar format. Figure 5 presents a composite of the wind errors (mean and standard deviation) over all runs for each phase. Figures 3 and 4 indicate a fair amount of variation in mean wind error from one flight to another, with small variation across the test runs within a flight as well as variation with altitude. In many cases, the errors exceed 10 m/s (approximately 20 knots, and large enough to cause a significant error in trajectory prediction), particularly in cruise where the trajectory error will accumulate over the time horizon of a typical trajectory prediction.



(a) Flight 678

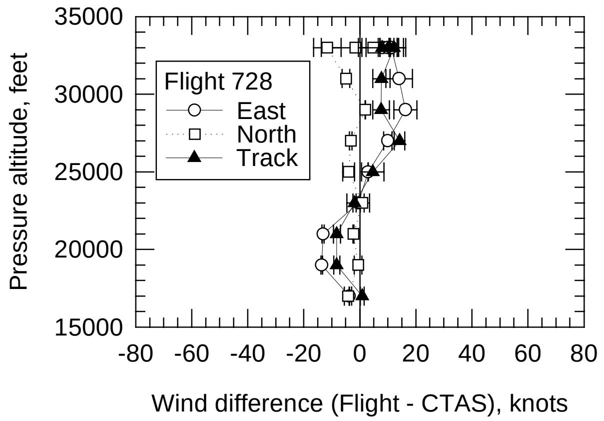


(b) Flight 680

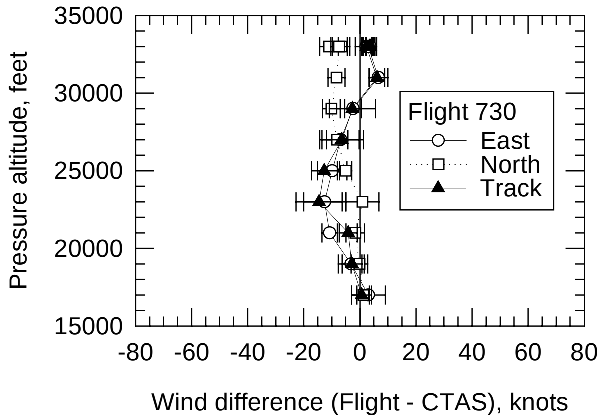


(c) Flight 682

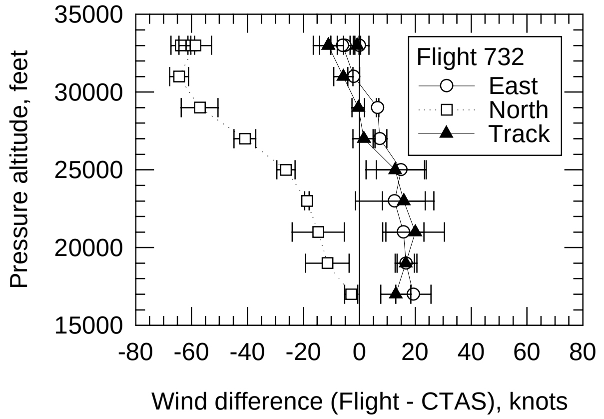
Figure 3. CTAS wind model errors from the phase I test.



(a) Flight 728



(b) Flight 730

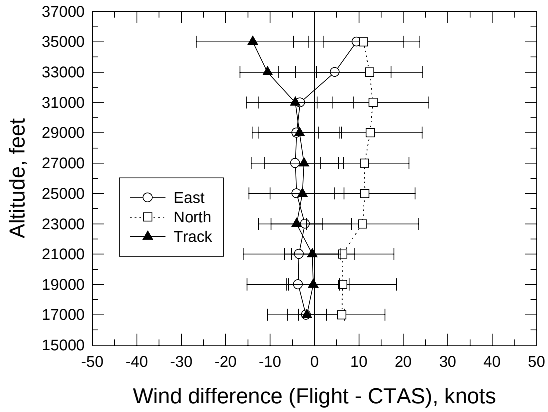


(c) Flight 732

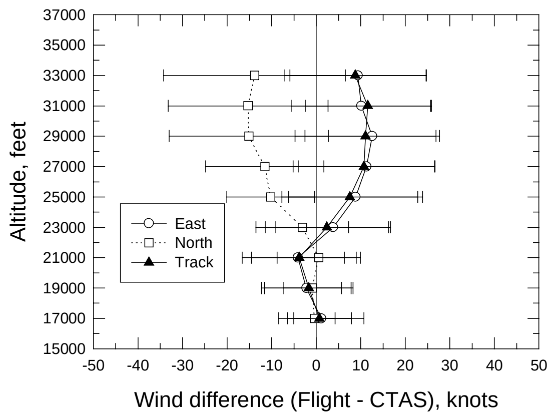
Figure 4. CTAS wind model errors from the phase II test.

In particular, the test runs within flight 732 (phase II) consistently experienced cruise wind errors greater than 30 m/s. This was attributed to a frontal passage in the general area that was incorrectly forecasted.

These flight test results reveal the existence of large wind prediction errors that may be detrimental to the performance of an ATM DST. Although these errors typically occur in scales of space and time that are critical to the performance of an ATM DST, they occur over scales that are much smaller than the spatial and temporal domains typically used to compute aggregate RMS error statistiscs and thus have little effect on typically reported accuracy statistics.



(a) Phase I test



(b) Phase II test

Figure 5. Composite CTAS wind model errors.

4. METRICS FOR LARGE ERRORS

For ATM applications, typically involving time horizons of 20-40 minutes, trajectory prediction errors in excess of 20-30 seconds may be disruptive and decrease the efficiency of ATM service (Green and Vivona, 1996; Paielli and Erzberger, 1996). In defining a metric for peak errors, it is useful to consider that the FAA standard for en route radar separation is 5 nmi. under Instrument Flight Rules (IFR). A 15 kt (~7.7 m/s) mean error in along-track head wind component, over a 20-minute trajectory prediction, will result in a 5 nmi. error in predicted position. For conflict prediction, trajectories are along different directions, and two trajectories will have different prediction errors which may sum to a larger error in aircraft separation than the individaul errors in aircraft location. In the worst case of aircraft converging from opposite directions, the errors in location will be of opposite sign, and the error in predicted aircraft separation will be twice the error in the individual aircraft locations. In the case of conflict prediction, much smaller mean along-track errors may lead to poor ATM DST performance than for the simpler task of aircraft sequencing.

While headwind error is the most appropriate wind error to study if examining time-to-fly errors for a given aircraft, it is easier to examine the magnitude of the vector error, as this is independent of any knowledge of specific trajectories. Given a wind vector error, an aircraft flying perpendicular to the error vector will experience no headwind error. An aircraft flying parallel to the error vector will experience a headwind error equal to the magnitude of the error vector. Averaged over all directions, the mean headwind error will be the magnitude of the error vector times $2/\pi$. Thus, a 15 kt headwind error is roughly equivalent to a 20 kt (~10m/s) vector error.

An ATM DST that provides active advisories (i.e., specific clearance suggestions for conflict resolution and flow-rate conformance), must provide high quality advisories at nearly all times. Even the occasional occurrence of incorrect advisories may not be operationally acceptable to controllers using the DST.

Standard measures of wind prediction accuracy are averaged over large periods of time and airspace. Alone, such aggregate metrics are not enough to determine the suitability of a wind field prediction for use by an active ATM DST. Most wind prediction systems provide adequate on-average performance since most of the time, over most of the airspace, the wind is only slowly varying and thus is easy to predict. However, as shown in the flight tests, unacceptably large wind errors (i.e., errors greater than 10 m/s) may exist over smaller periods of time and regions of airspace than typically have been studied in the meteorological literature. These large errors, potentially unacceptable for active ATM DST operations, are simply drowned out in the classical aggregate statistics typically used to assess the skill of wind prediction systems.

Wind prediction errors are known at locations where aircraft measured winds are available for comparison with the predicted winds. Since the aircraft measurements are averaged over scales of a kilometer or less, these spot checks represent point errors. The error in the wind field as measured by comparison to aircraft winds may be due to a small-scale wind feature that is missing from the modeled wind or may be due to a more systematic error in the modeled wind. If the wind error is due to a small-scale wind feature, it will not have a large effect on the predicted aircraft trajectory. Ideally, the errors all along a flight path would be studied, but the density of aircraft-measured winds does not make this possible in general.

Three types of metrics are introduced in this study to capture and quantify large errors. The simplest metric, large point error percentage, simply quantifies the percentage of wind vector errors larger than some value; for example, 10 m/s. A second type of metric is to compute percentile values of the magnitude of wind vector errors. These percentile values give a probability distribution. The probability distribution has the advantage that no threshold is set in advance; each user of the data can choose their own threshold. While isolated large point errors have little effect on time-to-fly estimates, the reduction in large point errors is a useful measure of improvement of wind prediction skill for ATM DST use.

A third type of metric, large hourly error percentage, is more directly related to ATM DST performance. This metric is based on the frequency of occurrence of large errors in temporal and spatial domains of interest to ATM automation rather than the frequency of large point errors. While a large point error by itself will not cause a problem, a collection of such errors along a flight path will. The data are not dense enough in general to look at errors along individual flight paths. Instead, the 25th percentile, 50th percentile, and 75th percentile errors for the wind fields on an hourly basis are used. If the 25th percentile hourly error is greater than 10 m/s, then 75% of all the errors measured in that hour are greater than 10 m/s. Given that most of the errors in an hour are greater than 10 m/s, it is likely that the wind field for that hour would lead to poor ATM DST performance. If the 75th percentile error is large, only 25% of the reported errors in that hour are large, but if these errors tend to be located in one region of the airspace, they may cause poor ATM DST performance.

5. METHODOLOGY

To determine wind field accuracy, the wind fields are compared to a data set of independent aircraft wind measurements (ACARS). More than one million aircraft reports collected during a one-year period (12 months for MIT/LL and 13 months for FSL) starting 1 August 1996 are used. These aircraft reports are collected in a region approximately 1300 km on a side, centered on the Denver International Airport. Each aircraft report is independent of the RUC forecasts valid at the time the report was taken since it is taken after the data collection period for the RUC run. Similarly, the aircraft reports are independent of any Augmented Wind field generated before the reports are taken.

The FSL results are obtained by differencing the aircraft reports with the RUC-1 and RUC-2 forecast fields nearest in time. The Lincoln results are obtained by comparing each aircraft report to the most recent prior Augmented Wind field and comparing the aircraft report to the RUC-1 forecast used in that Augmented Wind field. The wind field value at an aircraft location is computed from the gridded values using linear interpolation in three dimensions. The differences between the aircraft report and wind field values are estimates of the point errors in the wind fields and are used to compute the desired statistics.

The spatial distribution of the aircraft data is shown in figure 6. These data are from May 1st, 1997, the day United Airlines began rapid ascent and descent reporting in support of this study. The increased reporting continued through the remainder of the study period. Data prior to this have a similar distribution but are less dense, with about 3000 reports per day instead of about 8000. Most of the reports are at cruising altitudes, with two-thirds of the reports associated with the grid levels at 200 mb and 250 mb. Approximately 11% of the reports are associated with levels at 300 mb and 350 mb. The remaining reports are roughly uniformly distributed among levels from 400 mb to 800 mb, and as seen in the figure, are from aircraft in a funnel-like region centered on the Denver airport.

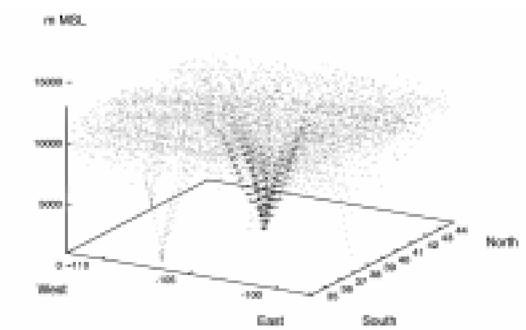


Figure 6. Distribution of ACARS reports on 1 May 1997. This day has 8125 ACARS reports. This is after United Airlines increased their reporting rate.

For these studies it is important to model the errors expected to be encountered by an ATM DST in computing time-of-flight as opposed to modeling random errors throughout the entire airspace. This is done by simply assuming that the distribution of aircraft reports in these studies is the likely distribution of aircraft an ATM DST will encounter. Therefore, the reported accuracy statistics are not quite measures of the overall accuracy of RUC or Augmented Winds. For example, these studies show that wind errors are greater at higher altitudes. Since there are more aircraft reports at higher altitudes, this tends to elevate the estimates of the RMS error in the wind fields relative to a uniformly distributed sample of errors. Conversely, there are more aircraft reports in regions where RUC and AW have dense aircraft input data, perhaps reducing the error estimates.

6. RESULTS

FSL found a RMS vector error of 5.26 m/s over all 0-6 hour RUC-1 forecasts, and a RMS vector error of 4.67 m/s for the same forecasts for RUC-2. These values are corrected for the errors in the aircraft reports and cover 13 months, 1 August 1996 through August 1997. Lincoln found a RMS vector error of 6.24 m/s for RUC-1 3-5 hour forecasts and a RMS vector error of 4.51 m/s for the Augmented Wind fields generated from these RUC-1 forecasts. These values are corrected for aircraft errors, and cover 12 months. A 16-day set of data were rerun using Augmented Winds fed RUC-2 instead of RUC-1. The improvement due to augmentation is essentially the same using either RUC-1 or RUC-2, so the improvement presented for the year-long Augmented Winds data set should represent the improvement over RUC-2 as well as over RUC-1. While there is a reduction in RMS error due to the improvement in the RUC model and due to the augmentation with near real-time aircraft reports, all of the RMS error values are well below 10 m/s. However, significant errors exist within individual forecasts.

Figure 7 shows the percentage of point errors for RUC-1 and RUC-2 that are greater than 10 m/s on a month-by-month basis over 13 months, starting in August 1996. The RUC-1 forecast fields are for predictions out 3-5 hours, as the forecasts are not available prior to hour three after the start of the model run. The RUC-2 forecast fields for hours 1 and 2 are used, as these are available before an hour after the start

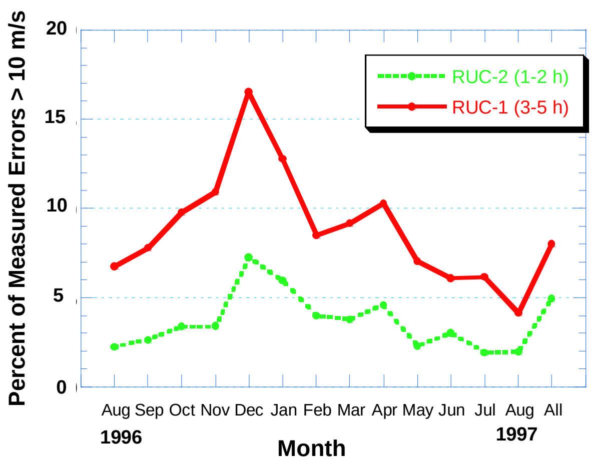


Figure 7. RUC Monthly RMS vector errors greater than 10 m/s.

of the model run. The percentage of large errors increases in the winter, corresponding to the increase in wind speed. The increase in error with with speed is due to a low bias in wind speed when the wind speeds are high. Potentially, an ATM system could correct for this bias to improve its performance. Due to the combination of shorter forecast times and improved RUC, the RUC-2 produces far fewer large point errors than RUC-1; 8% of the RUC-1 errors are greater than 10 m/s, while only. 3% of the RUC-2 errors are greater than 10 m/s.

Figure 8 provides probability distributions for RUC-1 and Augmented Winds (labled TW, or Terminal Winds, in the figure) over the entire data set. For example, the 90th percentile wind vector errors are 10.18 m/s and 7.85 m/s, respectively. The figure also indicates that RUC-1 forecasts contain vector errors greater than 10 m/s about 11% of the time; the augmentation with near real-time aircraft reports reduces the occurrence of errors greater than 10 m/s to 4% of the time.

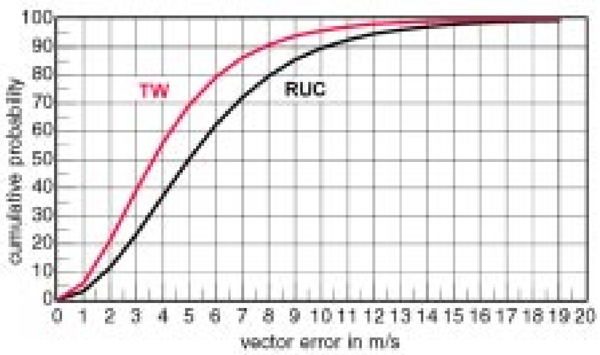


Figure 8. RUC-1 and TW (augmented RUC-1) cumulative probability vs. vector error.

Table 1 presents results for the same data set but using the third metric, large hourly error. For comparison, the results are presented in terms of the 25th, 50th and 75th percentile hourly-vector errors. Considering the 25th percentile division, it is seen that there are 42 hours during the year when 75 percent of the RUC-1 vector errors exceed 7 m/s. These 42 hours are evenly divided between nighttime and daytime and usually occur as isolated hours. The results indicate that augmenting RUC with near real-time aircraft reports reduces this number to five hours. There are no hours when 75 percent of the RUC-1 vector errors are greater than 10 m/s. Considering the 50th percentile division, the augmentation reduces the number of hourly vector errors greater than 7 m/s from 829 (RUC-1) to 124. Even more significant is the reduction of the number of hourly vector errors greater than 10 m/s from 46 hours to one. These 46 hours were also evenly divided between nighttime and daytime and usually occur as isolated hours. Having large errors even over 25 percent of a forecast region is potentially of operational concern if these errors are sustained along a flight path rather than randomly distributed. The augmentation resulted in similar improvements over RUC-1 for the 75th percentile division; most notable is the reduction in the number of hourly vector errors greater than 15 m/s from 45 to 8. Again, these 45 hours are evenly divided between nighttime and daytime and usually occur as isolated hours.

Table 1. Number of hours with hourly Nth percentile vector errors above given thresholds. Results are for 7023 hours.

Variable	>7m/s	>10m/s	>15ms
RUC-1 25th percentile	42	0	0
AW 25th percentile	5	0	0
RUC-1 50th percentile	829	46	0
AW 50th percentile	124	1	0
RUC-1 75th percentile	4160	834	45
AW 75th percentile	1913	203	8

7. CONCLUSIONS

Large wind errors (i.e., vector errors greater than 10 m/s) may be detrimental to ATM DST performance, especially if they persist along flight paths. Flight tests demonstrated the existence of such large errors that are not captured by the classic RMS aggregate statistics typically used to assess the skill of wind prediction systems.

Three types of metrics for measuring large errors were introduced. The first looks at the percentage of point wind vector errors greater than a threshold. The second type uses percentile values of the wind vector error, or the related probability distribution for wind vector errors. The last type is based on hourly periods with a large fraction of errors greater than a threshold.

Two approaches to improving wind field accuracy, improving the numerical model, and updating forecasts with near real-time aircraft reports were examined in a year-long study of wind prediction accuracy over the Denver Center airspace. Both approaches not only improved the overall aggregate RMS performance, they also greatly reduced the occurrence of large errors as measured by each of the three metrics. An additional analysis of a representative subset of sixteen days demonstrated the potential performance enhancements of combining both approaches simultaneously. The parameters that govern the Augmented Winds algorithm were updated based on what was learned in this study. With the updated parameters, the improvement in RMS vector error of the augmented winds is essentially the same for both RUC-1 and RUC-2, indicating that the above results for AW are relevant for augmentation of the current operational RUC model. In other words, although RUC-2 provides a significant performance improvement over RUC-1 itself, the augmentation of RUC-2 with near real-time aircraft reports adds additional performance on par with the augmentation enhancement of RUC-1.

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Rodney E. Cole

Dr. Cole received his B.S. in physics in 1981 and his M.S. in mathematics in 1982, both from the Virginia Polytechnic Institute and State University. He received his Ph.D. in mathematics from the University of Colorado in 1990. Dr. Cole began his research in meteorology at the National Center for Atmospheric Research in 1988 studying wind shear detection. He joined MIT Lincoln Laboratory in 1990, developing the wind shear detection algorithm for integrating the anemometer based LLWAS system and the radar based system TDWR, for the FAA. His work continues in wind estimation for the FAA Integrated Terminal Weather System.

Steven Green

Mr. Green joined NASA Ames Research Center in 1985 as a research engineer for Air Traffic Management automation. One of the four CTAS "founders," he lead the development and field testing of the CTAS Descent Advisor (DA) and was the principal investigator for the development/evaluation of air-ground integration concepts, including CTAS-FMS integration, en-route trajectory negotiation, and data exchange to enable user-preferred trajectories. Mr. Green manages NASA's en route ATM research, co-leads NASA's Distributed Air-Ground research, and serves as the government co-chair of RTCA SC-194/WG-2 on FMS-ATM-AOC Integration. Mr. Green received a B.S. (Aeronautical and Mechanical Engineering) from the University of California at Davis in 1985, a M.S. degree in Aeronautics & Astronautics from Stanford University in 1988, and is an instrument-rated pilot.